White Matter Fiber Tracking Based on Multi-Directional Vector Field

Q. Zeng[1], W. Guo[1], Y. Chen[1], A. G. He[2], Y. Liu[2,3]

[1]Mathematics, University of Florida, Gainesville, Florida, United States, [2]Psychiatry, University of Florida, Gainesville, Florida, United States, [3]Neuroscience, McKnight Brain Institute, Gainesville, Florida, United States

Introduction

Numerous studies have addressed the problem of the estimation and regularization of diffusion tensor field, based on which white matter fiber tracts are created (1-3). However, the Gaussian model is inappropriate for assessing multiple fiber tract orientations (4-6). Here we present a variational framework for determination of smooth intra-voxel fiber orientations under the assumption of biGaussian diffusion as well as a novel algorithm for extracting fiber tracts based on multi-directional vector field.

Methods

Automatic fiber tract mapping problems will be solved in by two steps. First, a smooth 3D vector field is obtained by simultaneously estimating and regularizing two tensor fields. BiGaussian diffusion is modeled as $S = S_0(fe^{-bu^T D_1 u} + (1-f)e^{-bu^T D_2 u})$ (1.1), where f, 1-f are the volume fraction w.r.t tensor D_1, D_2 respectively.

Fractional anisotropy (FA) or the measure R_2 in (8) could be used to provide an estimation of f. As we know, voxels with very high FA or R_2 are of one fiber-diffusion, and those with very low FA or R_2 are of isotropic diffusion. In the union of these voxels, designated as Ω_1, single Gaussian diffusion model can be used and initial estimation of f is set to be 1 in Ω_1. Real D_1, D_2 and f can be determined by minimizing the following energy functional, where $u^T = (\sin\theta\cos\phi, \sin\theta\sin\phi, \cos\theta)$:

$$\min_{L_1, L_2, f} \int_{\Omega} \int_0^{2\pi} \int_0^{\pi} [S - S_0(fe^{-bu^T L_1^T L_1 u} + (1-f)e^{-bu^T L_2^T L_2 u})]^2 \sin\theta d\theta d\phi dx + \lambda \int_{\Omega} [\sum_{i=1}^{2} |\nabla L_i|^{P_l(x)} + |\nabla f|^{P_f(x)}] dx + \beta \int_{\Omega_1} (f-1)^2 dx \qquad (1.2)$$

Where $L_i L_i^T = D_i$, i=1,2, and diagonal elements of L_i, i=1,2 are required to be positive to guarantee the positive definiteness of each tensor. In model (1.2) the first one is the non-linear data fidelity term based on (1.1), the middle two terms regularize D_i and f, and the last term forces $f \approx 1$ on Ω_1. λ, β are parameters balancing fidelity and smoothing terms. Solutions of model (1.2) provide a smooth multi-tensor vector field, tractography based on which is almost not sensitive to noise and more accurate. Fibers are traced by using streamline propagation method in multi-directional vector field. Fiber tracking has been initiated from and constrained to voxels with higher anisotropy across the whole brain. Fiber traces are colored using laplacian eigenmaps(7). Healthy human subjects (N = 12) were scanned using a 3.0 Tesla GE MRI system. The raw diffusion-weighted images were obtained using a single shot spin- echo EPI sequence with TR/TE = 1000ms/85ms, FOV = 220mm2, matrix size = 128 x 128 (reconstructed to 256x256), NEX = 2 for reducing the overall time of the scanning. Diffusion-sensitizing gradients were applied in 55 directions with b = 1000 sec/mm2. Twenty-four transversal slices of 3.8 mm thickness (1.2 mm gap) were selected covering the whole brain.

Results

Fig.1shows the solution of f in a typical brain slice. We can see that $f \approx 1$ in the dark red regions, where voxels are classified as isotropic or one-fiber diffusion. To verify the accuracy of our model in recovering fiber directions, we selected a region in the internal capsule known as one fiber orientation. For each voxel in this region we computed the direction in which ADC(8) is maximized (shown in Fig.2a). The directions of the principle eigenvectors of D_1 are shown in Fig.2b. Our model solution matches this vector field and is much more smoother due to the regularization terms in the model (1.2). Fig.3 shows the shapes of the right hand side term of (1.1) at 3 particular voxels(2-fiber,1-fiber, isotropic diffusion respectively). The arrows indicate the orientations of fibers. Color representation of principal eigenvectors of D_1 and D_2 of a typical brain slice is depicted in Fig 4. In Fig5, color mapping of 6000 fibers embedded in a skull is demonstrated from axial, coronal and saggital view respectively and seeds are the voxels with higher anisotropy in the whole brain. Fig 6 shows tracts in the posterior corpus callosum, and seeds are those voxels with high anisotropy around the corpus callosum. Traces with similar mean and covariance, hence traces close to each other, are colored similarly.

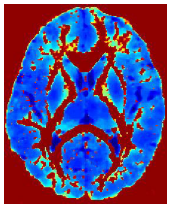

Fig 1

Fig 2a

Fig2b

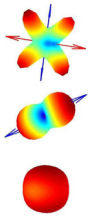

Fig 3

Fig 4a

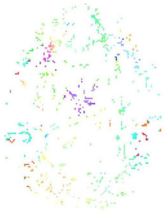

Fig 4b

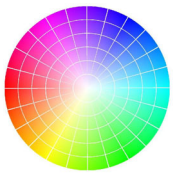

Fig 4c

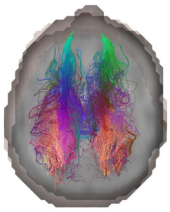

Fig5a Axial View

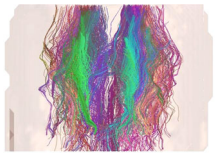

Fig5b Coronal View

Fig5c Saggital View

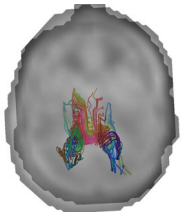

Fig6a Axial View

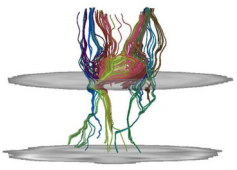

Fig6b Coronal View

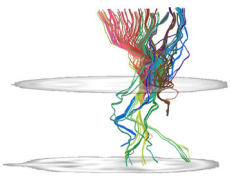

Fig6c Saggital View

Discussion

Our approach differs from the existing methods in the following aspects. First, we recover $D_1(x)$,$D_2(x)$ and $f(x)$ globally by simultaneous field smoothing and data fitting, rather than estimating them from (1.1) voxel by voxel which is an ill-posed problem. Second, isotropic, one-fiber and multi-fiber diffusion can be separated automatically by the model solution. Hence, this approach will be less sensitive to errors in the voxel classification. Third, our fiber tracking is based on a smooth multi-tensor vector field, which is not subject to noise and, therefore, more accurate.

Reference

(1) PJ Basser et al Biophy 66:259,1994. (2) CF Westin et al Med Img Ana 6:93,2002. (3) C Poupon et al Neuroimage 12: 184,2000.
(4) AL Alexander et al MRM 45: 770, 2001. (5) LR Frank ISMRM p1531, 2001. (6) DS Tuch et al ISMRM p321, 1999.
(7) M Belkin et al Advances in Neural Information Processing Systems 14, 2002. (8) Y Chen et al CVPR p588-593, 2004.